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Research Article

Real-Time Leak Detection in High Frequency Hydraulic Cylinder Based on Intelligent Control

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Most of the existing hydraulic cylinder internal leakage detection methods are laboratory testing methods, mainly the pressure-holding method, measurement of hydraulic cylinder settlement method, and measuring cup measurement method. The internal leakage of the hydraulic cylinder affects the damping characteristics of the control system. Therefore, real-time internal leakage detection plays an important role in the control characteristics. This paper first proposes a wavelet analysis-based extraction of hydraulic cylinder internal leakage fault eigenvalues for analysis, that is, data processing. A convolutional neural network-based detection method is also proposed, in which the pressure signal of a chamber of a hydraulic cylinder is first obtained through simulation under four operating conditions: no leakage, small leakage, medium leakage, and large leakage. Compared to traditional modelling methods, the method overcomes the difficulties in modelling nonlinear hydraulic systems, requires only pressure signal acquisition, is simple and reliable, and is compared with traditional BP neural networks to demonstrate its superiority.

1. Introduction

With the rapid development of modern industry, the ensuing requirements for transmission systems are becoming higher and higher, and this trend is becoming more and more prominent in various industries. And hydraulic systems with their fast response time, high load resistance stiffness, high power density, low speed stability, and other advantages are widely used in major fields and occupy a very important position [1]. Leakage is one of the common failures of electro-hydraulic servo systems and can cause problems such as insufficient hydraulic cylinder output, poor pressure-holding performance, reduced efficiency, and low load resistance stiffness, affecting the smoothness, reliability, and service life of hydraulic equipment. According to the location of fluid leakage, the leakage of hydraulic cylinders [2], the internal leakage is due to damage or failure of the piston or seal, and fluid is transferred from one chamber of the cylinder to another. For hydraulic systems, internal leakage in hydraulic cylinders can affect the dynamic balance of the system, making the pressure in the chamber insufficient to drive the load. Generally speaking, external leaks in hydraulic cylinders are easier to detect because of their visibility, whereas internal leaks are difficult to detect until the hydraulic system is not working properly due to their invisibility.

Hydraulic cylinders are important actuating elements of modern industrial equipment hydraulic systems, due to their simple structure, strong output capacity (force, torque, etc.), and high reliability, making them very widely used in heavy construction machinery, machine tools, walking machinery, and aerospace and other fields. Hydraulic cylinders usually work directly with the load, exposed to the working environment without any protection measures, the output of the displacement or output force acting directly on the load, so the hydraulic cylinder in the actual working conditions of the load conditions are very complex. Such harsh working conditions on the use of hydraulic cylinder performance put forward very strict requirements, the use of hydraulic cylinder performance often directly determine the entire mechanical equipment hydraulic system performance, and hydraulic cylinders are mainly applicable to the load-bearing capacity of special large machinery and equipment, if the use of hydraulic cylinder performance is not stable enough will easily lead to the failure of mechanical equipment or even a very serious accident disaster.

The types of hydraulic cylinder failure are very diverse, the main types of failure are crawling, shock, external leakage, internal leakage, insufficient thrust, working speed reduction, and so on [3]. Currently for hydraulic cylinder failure types, leakage (including internal leakage and external leakage) is one of the more common types of failure of hydraulic cylinders [4]. Internal leakage and external leakage are two different ways of leakage of hydraulic cylinders, the current national test standards for hydraulic cylinders and industry test standards for hydraulic cylinder leakage fault detection is also divided into internal leakage fault detection and external leakage fault detection of two types of test [5]. The hydraulic cylinder external leakage fault detection test method is mainly to detect the hydraulic cylinder end cap and cylinder barrel between the seal and the piston rod and end cap seal hydraulic oil leakage, the detection method is also relatively simple, while the hydraulic cylinder internal leakage fault detection method for the hydraulic cylinder piston movement to the end of its stroke, but the hydraulic cylinder internal leakage (internal leakage allows a small amount of existence, not more than the allowed value cannot be called a failure) for the use of hydraulic cylinder performance has a very big impact, the main danger of the hydraulic cylinder internal leakage failure is easy to cause the hydraulic cylinder crawl, insufficient thrust, speed decline and work instability, and other one or more of the failure. Therefore, the internal leakage failure of hydraulic cylinders has a very large potential hazard [6].

According to Pascal's basic principle, it is known that when internal leakage occurs in a hydraulic cylinder, the dynamic pressure inside the working chamber will also fluctuate, and when the internal leakage suddenly increases, the pressure fluctuation will be more obvious, and at the same time, considering the advantages that the price of the pressure sensor is relatively cheaper than that of the flow sensor, easy to install, and will not affect the pressure of the oil circuit [7]. This paper proposes a method to detect and analyze the pressure signal inside the hydraulic cylinder by signal in real time detection and analysis, and extract the fault characteristic quantity directly related to the internal leakage in the signal time-frequency characteristics, the authors of this paper obtained the pressure signal of the hydraulic cylinder under different leakage degrees through simulation, and then used the pressure signal as the input of the convolutional neural network, and obtained a high accuracy rate after learning, training, and testing [8]. Moreover, this method does not require modelling, which overcomes the defect that leakage models are difficult to establish accurately, and is convenient and reliable, and has strong application value; a real-time hydraulic cylinder internal leakage detection method that determines whether leakage occurs in a hydraulic cylinder by detecting and comparing the fault feature quantity [9].

2. Hydraulic Cylinder Internal Leakage Fault Detection Method

At present, the hydraulic cylinder leakage fault detection method is mainly the above-mentioned pressure-holding method and the measuring cup measurement method, etc., lacking in its working process of real-time detection methods [10]. Hydraulic cylinder internal leakage fault detection technology belongs to the scope of mechanical fault diagnosis technology, the current common mechanical fault diagnosis methods can be considered for the detection of hydraulic cylinder internal leakage fault detection methods [11, 12].

2.1. Model-Based Fault Diagnosis Methods. The main drawback of model-based fault diagnosis is that when creating a mathematical model of the object of study, it is necessary to deal with the dynamic performance of the object of study and the uncertainty of the model parameters caused by the nonlinear characteristics [13]. Therefore, it is often necessary to simplify the mathematical or physical model according to the actual working conditions of the object of study and to take approximate values of the parameters in order to reduce the difficulty of modelling and the workload of building the corresponding model.

2.2. Signal Processing Based Fault Diagnosis Methods. With the rapid development of high-precision sensors and modern fault diagnosis and detection technology, signal processing-based fault diagnosis and detection methods have been developed to a high degree of completeness. By monitoring the fluctuations of the output physical quantities such as vibration, output force, flow, displacement, and acceleration of the object of study, and by using relevant mathematical methods to describe the correlation between the amplitude, phase, frequency, and correlation of the detected output physical quantities and the specified system fault, the fault diagnosis and detection method analyses, judges, and processes the specific fault of the system, and finally obtains accurate detection methods for processing results [14].

2.3. Artificial Intelligence-Based Fault Diagnosis Methods. Artificial intelligence-based fault diagnosis methods essentially use electronic computers to simulate the main functions of the human brain, making full use of the experience and knowledge of experts in various fields to simulate the problem-solving ideas and methods of professionals [15], more efficient analysis and use of existing information related to system failures, and successful identification and prediction of the current operating state of the system.

This method also has the significant advantage of not needing to establish mathematical models for the research object compared with the previous two methods, and is more suitable for fault diagnosis and detection of large complex and nonlinear systems [16]. Sfarra and Regi [17] proposed a leakage fault diagnosis method based on BP neural network and the dynamic process of hydraulic system pressure as the analysis object [18]. Nishiumi et al. [19] combined the principal element analysis method

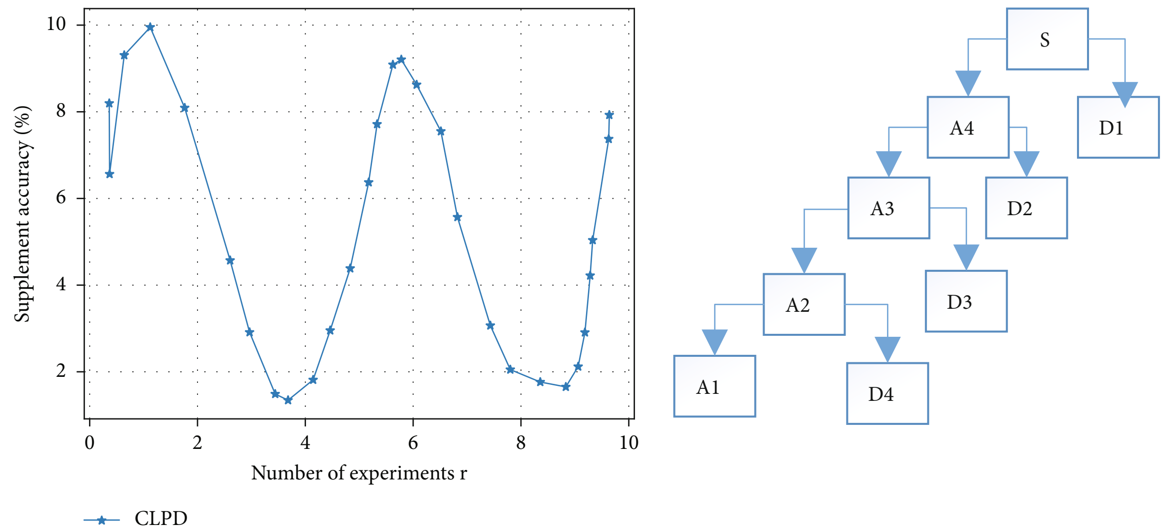

Figure 1: Wavelet transform analysis principle.

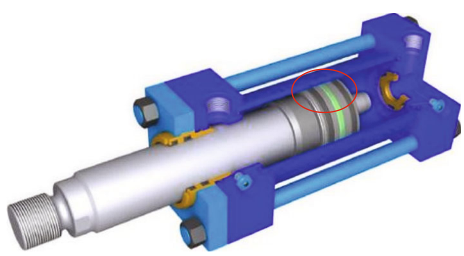

Figure 2: Schematic diagram of the principle of internal leakage in a hydraulic cylinder.

with BP neural network to detect the hydraulic cylinder leakage fault by using the pressure signal as the characteristic signal, which improved the diagnosis speed while meeting the fault detection recognition rate. A simulation study was carried out to investigate the leakage fault and oil filter blockage in the landing gear retracting system [20]. However, both SVM and BP neural network have shortcomings. On the one hand, SVM is difficult to solve the fundamental zero and nonzero problems; on the other hand, BP neural network is difficult to avoid the overfitting problem, which seriously restricts the application of neural network [21, 22].

3. Data Processing Based on Wavelet Analysis

The main task of signal analysis is to find a simple and efficient signal feature extraction method to obtain the feature quantity contained in the analyzed signal that is obviously helpful to solve the problem under study, and to solve the problem under study according to the feature quantity or its certain change trend. The pressure signal of the hydraulic oil in a hydraulic cylinder is a typical nonstationary signal due to the random jitter of the hydraulic oil leakage [23, 24]. The wavelet transform is a multiresolution signal processing method developed at the end of the 20th century. The theoretical approach of the wavelet transforms is to translate a basic wavelet function at different scales with time parameters and multiscale contraction that the wavelet transform uses a small region of waves with fast decay and a mean value of 0. The wavelet function is defined as following [25].

Assume that $\psi(t)$ is a square productable function, i.e. $\psi(t) \in L^2(R)$, and that the Fourier transform of $\psi(t)$yields $\psi(\omega)$ satisfying the basic conditions as shown in

$$0 < C_\psi = \int_R \frac{|\psi(\omega)|^2}{\omega} \mathrm{d}\omega < \infty. \tag{1}$$

$\psi(t)$ is called a basic wavelet function or wavelet master function and C_ψ is the permittivity constant. The continuous wavelet basis function $\psi_{a,\tau}(t)$ is obtained by scaling and time shifting the mother wavelet function $\psi(t)$by a series of scaling and time shifting

$$\psi_{a,\tau}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-\tau}{a}\right). \tag{2}$$

In equation (2), a is the scale scaling factor of the wavelet transform and τ is the translation factor or time factor of the wavelet transform.

The essence of wavelet transform is to decompose a set of wavelet mother functions $\psi(t)$ into approximate signals A1, A2, A3, …, An and detail signals D1, D2, D3, …, Dn in the form of basic functions at different frequency bands after time translation τ, as shown in Figure 1.

$$\psi_{j,k}(t) = a_0^{-j/2} \psi\left(a_0^{-j} t - k_0\right). \tag{3}$$

The discretized wavelet coefficients can be expressed as

$$c_{j,k} = \int_{-\infty}^{\infty} f(t) \psi_{j,k}^*(t) \mathrm{d}t = \left[f, \psi_{j,k}\right]. \tag{4}$$

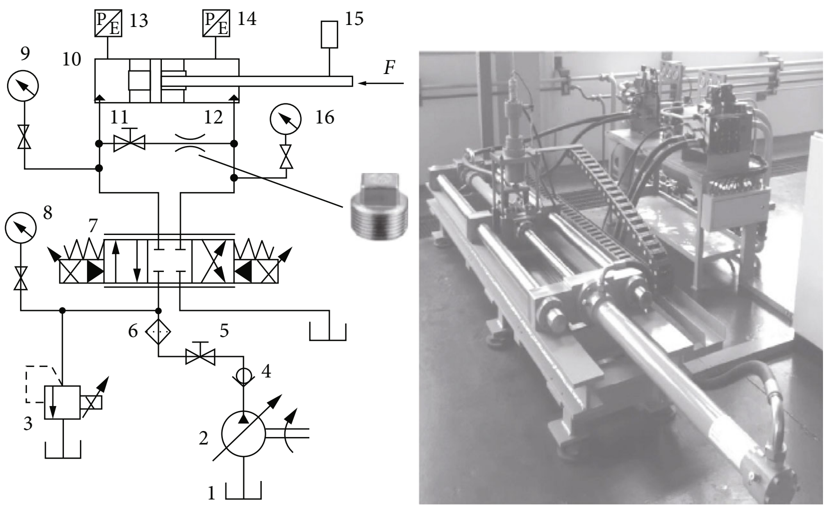

Figure 3: Hydraulic principle and experimental rig for the detection of internal leakage faults in hydraulic cylinders.

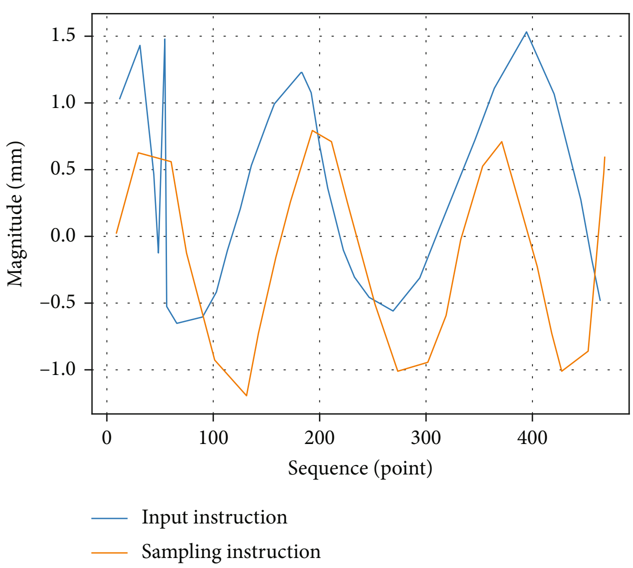

Figure 4: Input instructions and sampling instructions.

In this study, the main research problem is the internal leakage fault of hydraulic cylinder, through the wavelet transform of the pressure signal of the rodless cavity of the hydraulic cylinder measured in real time [26], the principle of the internal leakage of the hydraulic cylinder is shown in Figure 2.

The internal leakage of a hydraulic cylinder consists of two main components: the internal leakage caused by the oil film gap between the seal and the piston and the internal leakage caused by the oil film gap between the seal and the cylinder barrel. In the experimental process, in order to realistically simulate the hydraulic cylinder in the internal leakage fault state, the feasibility of using wavelet analysis to extract the characteristic quantity of internal leakage fault to detect the hydraulic cylinder internal leakage fault method was investigated, and the experimental system shown in Figure 3 was established. As shown in the hydraulic schematic diagram in Figure 3, the hydraulic cylinder was subjected to an internal leakage fault condition simulated by connecting a throttle hole 12 between the rod and rodless chambers of the hydraulic cylinder under test (the piston of the hydraulic cylinder under test has six seals between the piston and the cylinder barrel to ensure that the signal fluctuation is caused by the internal leakage of the throttle hole 12), and the hydraulic cylinder under test was fixed horizontally on the experimental bench. The piston rod of the hydraulic cylinder under test was subjected to a load F. The load F was adjusted by adjusting the pressure of the rodless chamber of the top cylinder to ensure that the pressure of the rodless chamber of the hydraulic cylinder under test was 20 MPa, and the hydraulic cylinder under test was run back and forth several times. The output is the pressure signal of the rodless chamber of the hydraulic cylinder s.

In this paper, the ARC controller model is used to simulate the pressure signals on both sides of the hydraulic cylinder.

After wavelet transforms processing, the input command is a sinusoidal signal with an amplitude of 2 mm and a period of 0.05 s, as shown in Figure 4, with a sampling frequency of 20 Hz.

Four different operating conditions are simulated, no leakage, small leakage, medium leakage, and large leakage. The pressure signal is simulated for 1,000 cycles for each condition, for a total of 4,000 cycles.

In this paper, only p1 (the so-called pressure signal p1) is used, and one pressure cycle for each condition is shown in Figure 5.

4. Convolutional Neural Networks

Generally speaking, for the application of convolutional neural networks, the input is a two-dimensional matrix. In this paper, the pressure signal obtained through simulation is one-dimensional, in order to better deal with the use of CNN, in MATLAB, the one-dimensional signal matrix is transformed into a two-dimensional matrix, the transformation principle is shown in Figure 6.

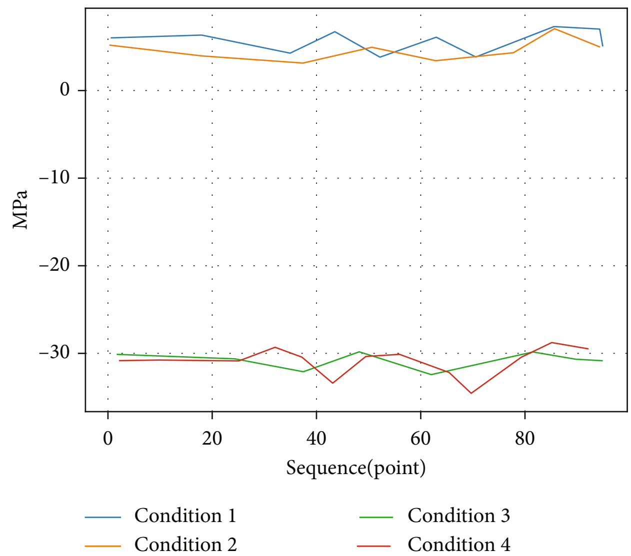

FIGURE 5: Pressure signals obtained from the simulation for different leakage levels.

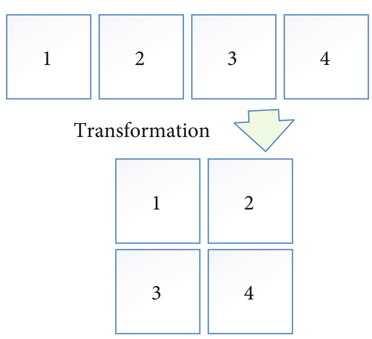

FIGURE 6: Principle of matrix transformation.

By this process, the original pressure simulation signal is transformed into a two-dimensional matrix, and then the resulting two-dimensional matrix is used as input to a CNN, the structure of which is shown in Figure 7.

In the training process, 3200 samples are randomly selected from 4000 samples as training samples and another 800 samples as test samples.

5. Experiment

The learning rate is set to 2, 50 samples are trained at a time, 200 iterations in total, and the error curve is shown in Figure 8.

The correctness rate obtained in the paper was tested and was 97.125%. In addition, the data obtained were tested using a conventional BP neural network with three layers. The input layer has 100 neurons corresponding to 100 points in the sample signal, the output layer has 4 neurons corresponding to 4 different levels of leakage, and the hidden layer has 80 neurons with a learning rate of 2. The same 200 iterations, with a bias of b, give a correct rate of 92.25% as showing in Table 1.

Five hydraulic plugs were drilled with 0.1, 0.2, 0.3, 0.4, and 0.5 mm holes to be used as the throttle holes of the test system. The db6 wavelet was used to decompose and reconstruct the pressure signal s (sampling frequency 1000 Hz) in the rodless cavity of the hydraulic cylinder, and obtained the approximate low frequency signal a4 and the detailed (high frequency) signals d1, d2, d3, and d4 as shown in Figure 9.

With the increasing amount of leakage in the hydraulic cylinder, the leakage fault in the hydraulic cylinder will become more and more serious, and the flow rate in the hydraulic cylinder will inevitably decrease, which will lead to a slowing down of the hydraulic oil pressure rise in the rodless chamber of the hydraulic cylinder, also expressed as a continuous loss of hydraulic energy [27].

The approximate low-frequency signal a4 is a low-frequency component relative to the acquired pressure signal s. From the point of view of signal analysis, the energy value of the low-frequency signal a4 is so large that it can be used as an amplitude modulation signal for signal processing, and the low-frequency signal is not conducive to comparison with the high-frequency band detail signal. Therefore, the low frequency signal is no longer included in the calculation of the wavelet energy for the different internal leakage fault states of the hydraulic cylinder under test [28]. Wavelet energy values at different scalesE_j (j = 1, 2, 3, 4) are calculated as follows:

$$E_j = \int \left|d_j\right|^2 \mathrm{d}t = \sum_{k=1}^{n} \left|x_{j,k}\right|^2, \tag{5}$$

where $d_j(t)$ represents the reconstructed jth level of detail signal and $x_{j,k}(k = 0, 1, \cdots, n)$represents the discrete point amplitude of the detail signal d_j. Considering that E_j is usually a large value, which can cause some inconvenience in the analysis process, the energy of the pressure detail signals

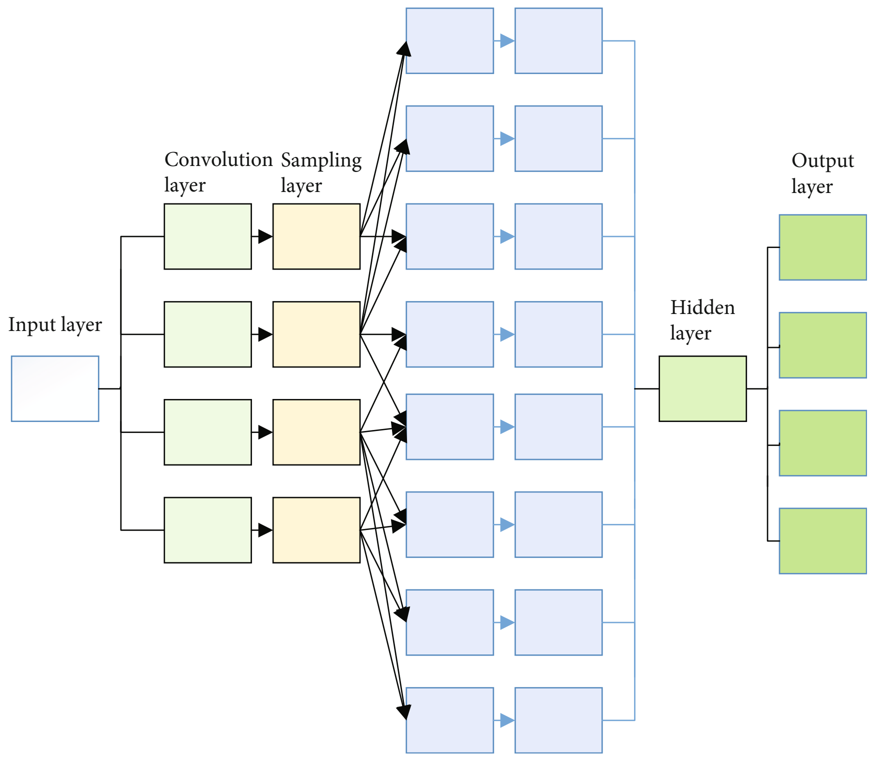

Figure 7: Structure of the CNN used.

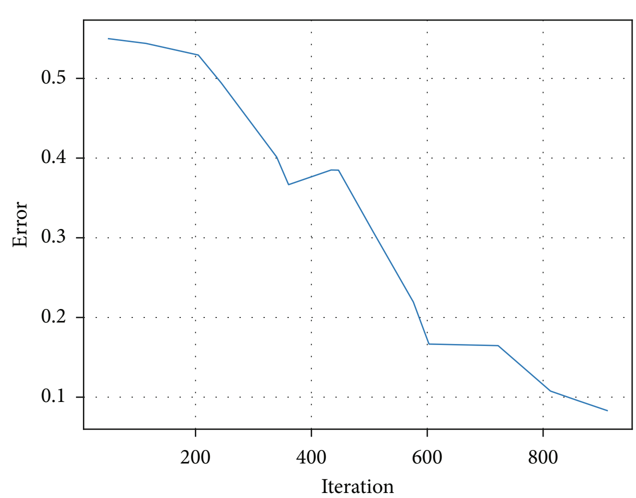

Figure 8: Error curves.

Table 1: Comparison of correct rates.

Neural network	Accuracy/%
Convolutional neural network	97.125
BP neural network terminal	92.25

d1, d2, d3, and d4 at different leakage levels are calculated and then, normalized in a uniform way to obtain the relative wavelet energy $p_j = E_j/(E_1 + E_2 + E_3 + E_4)$ at each scale, as shown in Table 2.

From the analysis of the data in Table 2, it can be seen that the wavelet energy value obtained from the decomposition and reconstruction of the detailed signal d4 of the rodless cavity pressure signal is gradually decreasing as the leakage volume in the hydraulic cylinder under test increases, under the condition that the supply pressure of the hydraulic cylinder remains unchanged, as shown in Figure 10. This simulates the increasing amount of leakage in the hydraulic cylinder under test, and the work done by the hydraulic cylinder rodless cavity pressure fluid on the piston decreases, and the operating speed of the hydraulic cylinder slows down. In summary, the calculated energy value of the fourth wavelet decomposition detail signal d4 of the rodless cavity pressure signal of the hydraulic cylinder under test is used as the fault characteristic quantity of the internal leakage fault of the hydraulic cylinder, and it is compared with the set fault threshold to determine the occurrence of the internal leakage fault, so as to achieve the accurate detection of the hydraulic cylinder fault, through the experimental discussion in this section, it is illustrated that the use of wavelet analysis based method to extract the fault characteristic quantity of the internal leakage of the hydraulic cylinder. Through the experimental discussion in this section, it is shown that the method of using wavelet analysis to extract the fault characteristic quantity of hydraulic cylinder internal leakage—the detail signal to calculate the energy value for the detection of hydraulic cylinder internal leakage fault is feasible and has application value, the detection method can provide an effective basis for the detection of hydraulic cylinder internal leakage fault and has certain practical application value [29].

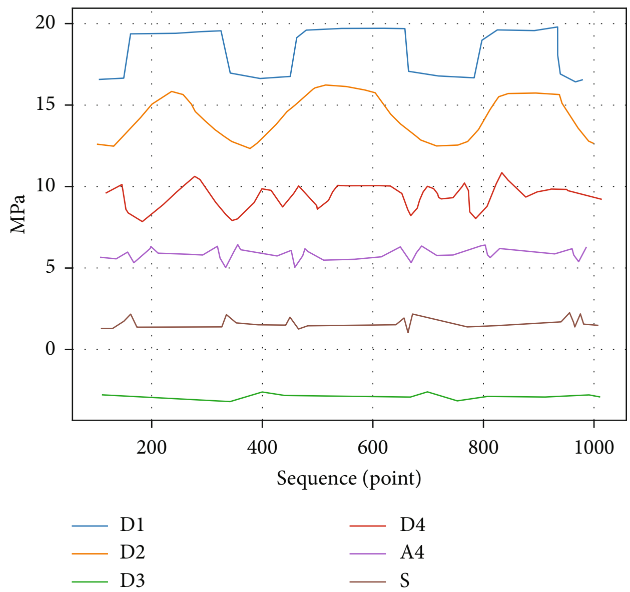

FIGURE 9: 4-layer wavelet decomposition of the pressure signal.

TABLE 2: Wavelet energy of rodless cavity pressure signals.

Serial number	Orifice specification/mm	P1	P2	P3	P4
1	0	0.0675	0.1096	0.2	06228
2	0.1	0.1756	0.1040	0.1842	0.5362
3	0.2	0.1498	0.0986	0.2530	0.5362
4	0.3	0.2071	0.1060	0.2496	0.4327
5	0.4	0.2793	0.2	0.1798	0.3708
6	0.5	0.2449	0.1820	0.2563	0.3167

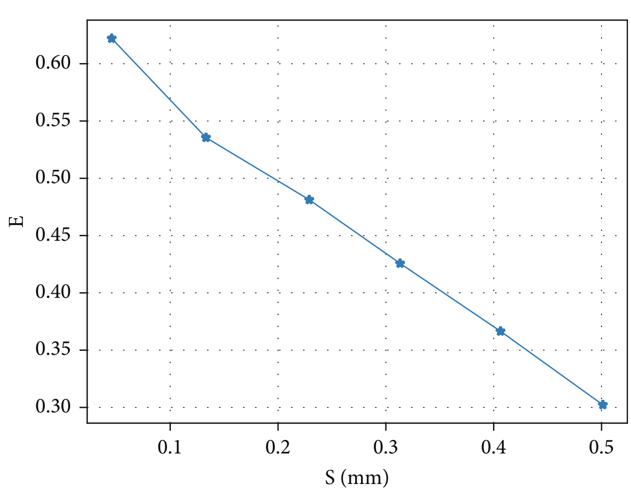

FIGURE 10: Rodless cavity pressure detail signal d4 wavelet energy values.

6. Conclusions

For the current hydraulic cylinder internal leakage detection method can only be detected in the laboratory and cannot be detected in the working process of the hydraulic cylinder limitations, this study proposed a wavelet analysis-based hydraulic cylinder internal leakage fault detection method in real time, through the experimental equipment to obtain experimental data and data analysis of experimental data can be concluded as follows:

(1) The use of wavelet analysis for fault detection of internal leakage of hydraulic cylinders does not depend on the precise mathematical model of hydraulic cylinders, the detection method is simpler, easier to implement, lower cost, and can be monitored and detected in real time during the work of hydraulic cylinders

(2) The feasibility of wavelet analysis in hydraulic cylinder internal leakage fault detection is verified through experiments and analysis, which shows that the wavelet analysis-based hydraulic cylinder internal leakage fault detection technology can be applied in practical engineering, and the method is of great practical significance for hydraulic cylinder internal leakage fault detection

Data Availability

The datasets used during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interests.

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